Application of Deep Neural Network for Image Classification:

1 - Packages

First import all the packages that will be needed during this project.

- numpy is the fundamental package for scientific computing with Python.
- matplotlib is a library to plot graphs in Python.
- h5py is a common package to interact with a dataset that is stored on an H5 file.
- PIL and scipy are used here to test our model with our own picture at the end.
- np.random.seed(1) is used to keep all the random function calls consistent.

In [1]:
```
import time
import numpy as np
import h5py
import matplotlib.pyplot as plt
import scipy
from PIL import Image
from scipy import ndimage
from dnn_app_utils_v2 import *
from dnn_app_utils_v3 import *

%matplotlib inline
plt.rcParams['figure.figsize'] = (5.0, 4.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

%load_ext autoreload
%autoreload 2

np.random.seed(1)
```

2 - Dataset

The dataset containing:

```
- a training set of m_train images labelled as cat (1) or non-cat (0)
- a test set of m_test images labelled as cat and non-cat
- each image is of shape (num_px, num_px, 3) where 3 is for the 3 channels (RGB).
```

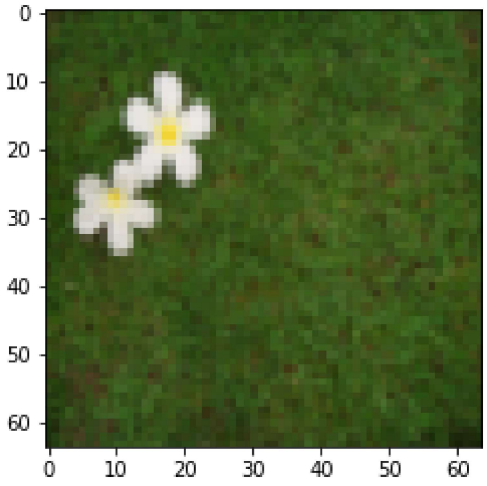
Load the data by running the cell below.

In [2]:
```
train_x_orig, train_y, test_x_orig, test_y, classes = load_data()
```

The following code will show an image in the dataset. Change the index and re-run the code multiple times to see other images.

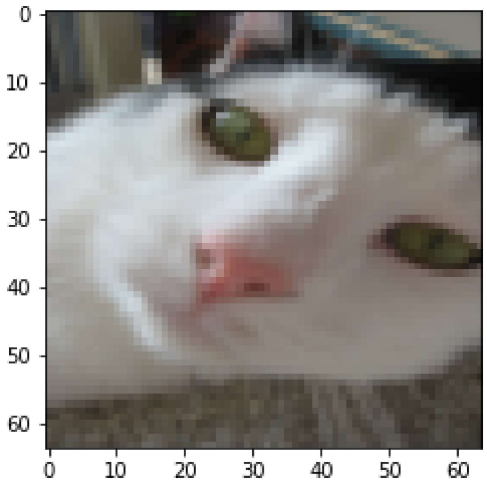
In [3]:
```
# Example of a picture
index = 6
plt.imshow(train_x_orig[index])
print ("y = " + str(train_y[0,index]) + ". It's a " + classes[train_y[0,index
]].decode("utf-8") +  " picture.")
```

```
y = 0. It's a non-cat picture.
```



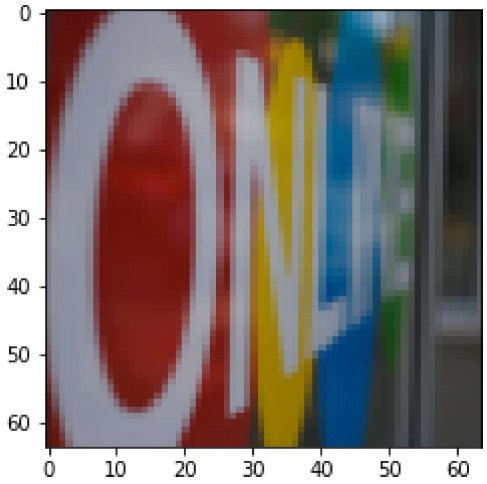
In [4]:
```
# Example of a picture
index = 14
plt.imshow(train_x_orig[index])
print ("y = " + str(train_y[0,index]) + ". It's a " + classes[train_y[0,index
]].decode("utf-8") +  " picture.")
```

```
y = 1. It's a cat picture.
```



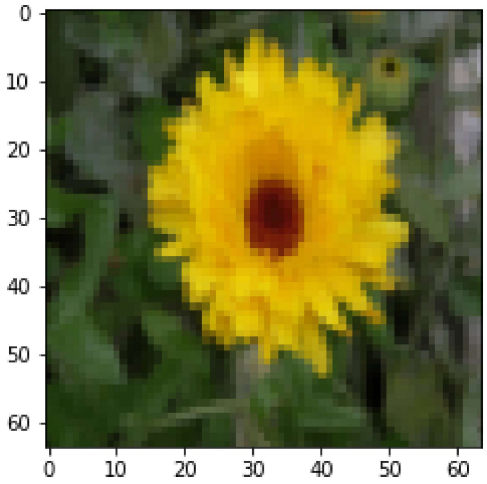
In [5]:
```
# Example of a picture
index = 49
plt.imshow(train_x_orig[index])
print ("y = " + str(train_y[0,index]) + ". It's a " + classes[train_y[0,index
]].decode("utf-8") +  " picture.")
```

```
y = 0. It's a non-cat picture.
```



In [6]:
```
# Example of a picture
index = 160
plt.imshow(train_x_orig[index])
print ("y = " + str(train_y[0,index]) + ". It's a " + classes[train_y[0,index
]].decode("utf-8") +  " picture.")
```

```
y = 0. It's a non-cat picture.
```



In [7]:
```
# Explore dataset
m_train = train_x_orig.shape[0]
num_px = train_x_orig.shape[1]
m_test = test_x_orig.shape[0]

print ("Number of training examples: " + str(m_train))
print ("Number of testing examples: " + str(m_test))

print ("Each image is of size: (" + str(num_px) + ", " + str(num_px) + ", 3)")
print ("train_x_orig shape: " + str(train_x_orig.shape))
print ("train_y shape: " + str(train_y.shape))
print ("test_x_orig shape: " + str(test_x_orig.shape))
print ("test_y shape: " + str(test_y.shape))
```

```
Number of training examples: 209
Number of testing examples: 50
Each image is of size: (64, 64, 3)
train_x_orig shape: (209, 64, 64, 3)
train_y shape: (1, 209)
test_x_orig shape: (50, 64, 64, 3)
test_y shape: (1, 50)
```

Reshape and standardize the images before feeding them to the network:

In [8]:
```
# Reshape the training and test examples
train_x_flatten = train_x_orig.reshape(train_x_orig.shape[0], -1).T   # The "-
1" makes reshape flatten the remaining dimensions
test_x_flatten = test_x_orig.reshape(test_x_orig.shape[0], -1).T

# Standardize data to have feature values between 0 and 1.
train_x = train_x_flatten/255.
test_x = test_x_flatten/255.

print ("train_x's shape: " + str(train_x.shape))
print ("test_x's shape: " + str(test_x.shape))
```

```
train_x's shape: (12288, 209)
test_x's shape: (12288, 50)
```

$12,288$12,288 equals $64 \times 64 \times 3$ 64×64×3 which is the size of one reshaped image vector.

3 - Architecture of model

Now it is time to build a deep neural network to distinguish cat images from non-cat images.

We will build two different models:

- A 2-layer neural network
- An L-layer deep neural network

We will then compare the performance of these models, and also try out different values for LL.

3.1 - 2-layer neural network

Detailed Architecture:

- The input is a (64,64,3) image which is flattened to a vector of size $(12288, 1)$ (12288,1).
- The corresponding vector: $[x_0, x_1, \ldots, x_{12287}]^T$ [x0,x1,...,x12287]T is then multiplied by the weight matrix $W^{[1]}$W[1] of size $(n^{[1]}, 12288)$ (n[1],12288).
- Then add a bias term and take its relu to get the following vector: $[a_0^{[1]}, a_1^{[1]}, \ldots, a_{n^{[1]}-1}^{[1]}]^T$ [a0[1],a1[1],...,an[1]−1[1]]T.
- Then repeat the same process.
- Multiply the resulting vector by $W^{[2]}$W[2] and add intercept (bias).
- Finally, take the sigmoid of the result. If it is greater than 0.5, classify it to be a cat.

3.2 - L-layer deep neural network

Detailed Architecture:

- The input is a (64,64,3) image which is flattened to a vector of size (12288,1).
- The corresponding vector: $[x_0, x_1, \ldots, x_{12287}]^T$ [x0,x1,...,x12287]T is then multiplied by the weight matrix $W^{[1]}$W[1] and then add the intercept $b^{[1]}$b[1]. The result is called the linear unit.
- Next, take the relu of the linear unit. This process could be repeated several times for each $(W^{[l]}, b^{[l]})$ (W[l],b[l])depending on the model architecture.
- Finally, take the sigmoid of the final linear unit. If it is greater than 0.5, classify it to be a cat.

3.3 - General methodology

As usual we follow the Deep Learning methodology to build the model:

```
1. Initialize parameters / Define hyperparameters
2. Loop for num_iterations:
    a. Forward propagation
    b. Compute cost function
    c. Backward propagation
    d. Update parameters (using parameters, and grads from backprop)
4. Use trained parameters to predict labels
```

In [9]:
```
# Create helper functions that will initialize the parameters for our models.

def sigmoid(Z):
    """
    Implements the sigmoid activation in numpy

    Arguments:
    Z -- numpy array of any shape

    Returns:
    A -- output of sigmoid(z), same shape as Z
    cache -- returns Z as well, useful during backpropagation
    """

    A = 1/(1+np.exp(-Z))
    cache = Z

    return A, cache

def relu(Z):
    """
    Implement the RELU function.

    Arguments:
    Z -- Output of the linear layer, of any shape

    Returns:
    A -- Post-activation parameter, of the same shape as Z
    cache -- a python dictionary containing "A" ; stored for computing the bac
kward pass efficiently
    """

    A = np.maximum(0,Z)

    assert(A.shape == Z.shape)

    cache = Z
    return A, cache


def relu_backward(dA, cache):
    """
    Implement the backward propagation for a single RELU unit.

    Arguments:
    dA -- post-activation gradient, of any shape
    cache -- 'Z' where we store for computing backward propagation efficiently

    Returns:
    dZ -- Gradient of the cost with respect to Z
    """

    Z = cache
    dZ = np.array(dA, copy=True) # just converting dz to a correct object.

    # When z <= 0, you should set dz to 0 as well.
```

```
    dZ[Z <= 0] = 0

    assert (dZ.shape == Z.shape)

    return dZ

def sigmoid_backward(dA, cache):
    """
    Implement the backward propagation for a single SIGMOID unit.

    Arguments:
    dA -- post-activation gradient, of any shape
    cache -- 'Z' where we store for computing backward propagation efficiently

    Returns:
    dZ -- Gradient of the cost with respect to Z
    """

    Z = cache

    s = 1/(1+np.exp(-Z))
    dZ = dA * s * (1-s)

    assert (dZ.shape == Z.shape)

    return dZ


def load_data():
    train_dataset = h5py.File('datasets/train_catvnoncat.h5', "r")
    train_set_x_orig = np.array(train_dataset["train_set_x"][:]) # your train
 set features
    train_set_y_orig = np.array(train_dataset["train_set_y"][:]) # your train
 set labels

    test_dataset = h5py.File('datasets/test_catvnoncat.h5', "r")
    test_set_x_orig = np.array(test_dataset["test_set_x"][:]) # your test set
 features
    test_set_y_orig = np.array(test_dataset["test_set_y"][:]) # your test set
 labels

    classes = np.array(test_dataset["list_classes"][:]) # the list of classes

    train_set_y_orig = train_set_y_orig.reshape((1, train_set_y_orig.shape[0
]))
    test_set_y_orig = test_set_y_orig.reshape((1, test_set_y_orig.shape[0]))

    return train_set_x_orig, train_set_y_orig, test_set_x_orig, test_set_y_ori
g, classes


# Create and initialize the parameters of the 2-layer neural network.
def initialize_parameters(n_x, n_h, n_y):
    """
    Argument:
    n_x -- size of the input layer
    n_h -- size of the hidden layer
```

```
    n_y -- size of the output layer

    Returns:
    parameters -- python dictionary containing your parameters:
                    W1 -- weight matrix of shape (n_h, n_x)
                    b1 -- bias vector of shape (n_h, 1)
                    W2 -- weight matrix of shape (n_y, n_h)
                    b2 -- bias vector of shape (n_y, 1)
    """

    np.random.seed(1)

    W1 = np.random.randn(n_h, n_x)*0.01
    b1 = np.zeros((n_h, 1))
    W2 = np.random.randn(n_y, n_h)*0.01
    b2 = np.zeros((n_y, 1))

    assert(W1.shape == (n_h, n_x))
    assert(b1.shape == (n_h, 1))
    assert(W2.shape == (n_y, n_h))
    assert(b2.shape == (n_y, 1))

    parameters = {"W1": W1,
                  "b1": b1,
                  "W2": W2,
                  "b2": b2}

    return parameters


# Implement initialization for an L-layer Neural Network.
def initialize_parameters_deep(layer_dims):
    """
    Arguments:
    layer_dims -- python array (list) containing the dimensions of each layer
 in our network

    Returns:
    parameters -- python dictionary containing your parameters "W1", "b1",
 ..., "WL", "bL":
                    Wl -- weight matrix of shape (layer_dims[l], layer_dims[l-
1])
                    bl -- bias vector of shape (layer_dims[l], 1)
    """

    np.random.seed(1)
    parameters = {}
    L = len(layer_dims)            # number of layers in the network

    for l in range(1, L):
        parameters['W' + str(l)] = np.random.randn(layer_dims[l], layer_dims[l
-1]) / np.sqrt(layer_dims[l-1]) #*0.01
        parameters['b' + str(l)] = np.zeros((layer_dims[l], 1))

        assert(parameters['W' + str(l)].shape == (layer_dims[l], layer_dims[l-
1]))
        assert(parameters['b' + str(l)].shape == (layer_dims[l], 1))
```

```
    return parameters


## Forward propagation
# Build the linear part of forward propagation.
def linear_forward(A, W, b):
    """
    Implement the linear part of a layer's forward propagation.

    Arguments:
    A -- activations from previous layer (or input data): (size of previous la
yer, number of examples)
    W -- weights matrix: numpy array of shape (size of current layer, size of
 previous layer)
    b -- bias vector, numpy array of shape (size of the current layer, 1)

    Returns:
    Z -- the input of the activation function, also called pre-activation para
meter
    cache -- a python dictionary containing "A", "W" and "b" ; stored for comp
uting the backward pass efficiently
    """

    Z = W.dot(A) + b

    assert(Z.shape == (W.shape[0], A.shape[1]))
    cache = (A, W, b)

    return Z, cache


# Implement the forward propagation of the LINEAR->ACTIVATION layer.
def linear_activation_forward(A_prev, W, b, activation):
    """
    Implement the forward propagation for the LINEAR->ACTIVATION layer

    Arguments:
    A_prev -- activations from previous layer (or input data): (size of previo
us layer, number of examples)
    W -- weights matrix: numpy array of shape (size of current layer, size of
 previous layer)
    b -- bias vector, numpy array of shape (size of the current layer, 1)
    activation -- the activation to be used in this layer, stored as a text st
ring: "sigmoid" or "relu"

    Returns:
    A -- the output of the activation function, also called the post-activatio
n value
    cache -- a python dictionary containing "linear_cache" and "activation_cac
he";
             stored for computing the backward pass efficiently
    """

    if activation == "sigmoid":
        # Inputs: "A_prev, W, b". Outputs: "A, activation_cache".
```

```
        Z, linear_cache = linear_forward(A_prev, W, b)
        A, activation_cache = sigmoid(Z)

    elif activation == "relu":
        # Inputs: "A_prev, W, b". Outputs: "A, activation_cache".
        Z, linear_cache = linear_forward(A_prev, W, b)
        A, activation_cache = relu(Z)

    assert (A.shape == (W.shape[0], A_prev.shape[1]))
    cache = (linear_cache, activation_cache)

    return A, cache


# Implement the forward propagation of the L-layer model.
def L_model_forward(X, parameters):
    """
    Implement forward propagation for the [LINEAR->RELU]*(L-1)->LINEAR->SIGMOI
D computation

    Arguments:
    X -- data, numpy array of shape (input size, number of examples)
    parameters -- output of initialize_parameters_deep()

    Returns:
    AL -- last post-activation value
    caches -- list of caches containing:
                every cache of linear_relu_forward() (there are L-1 of them, i
ndexed from 0 to L-2)
                the cache of linear_sigmoid_forward() (there is one, indexed L
-1)
    """

    caches = []
    A = X
    L = len(parameters) // 2                  # number of layers in the neural
network

    # Implement [LINEAR -> RELU]*(L-1). Add "cache" to the "caches" list.
    for l in range(1, L):
        A_prev = A
        A, cache = linear_activation_forward(A_prev, parameters['W' + str(l)],
parameters['b' + str(l)], activation = "relu")
        caches.append(cache)

    # Implement LINEAR -> SIGMOID. Add "cache" to the "caches" list.
    AL, cache = linear_activation_forward(A, parameters['W' + str(L)], paramet
ers['b' + str(L)], activation = "sigmoid")
    caches.append(cache)

    assert(AL.shape == (1,X.shape[1]))

    return AL, caches


# Compute the cross-entropy cost  J.
def compute_cost(AL, Y):
```

```
    """
    Implement the cost function defined by equation (7).

    Arguments:
    AL -- probability vector corresponding to your label predictions, shape
 (1, number of examples)
    Y -- true "label" vector (for example: containing 0 if non-cat, 1 if cat),
shape (1, number of examples)

    Returns:
    cost -- cross-entropy cost
    """

    m = Y.shape[1]

    # Compute loss from aL and y.
    cost = (1./m) * (-np.dot(Y,np.log(AL).T) - np.dot(1-Y, np.log(1-AL).T))

    cost = np.squeeze(cost)      # To make sure your cost's shape is what we e
xpect (e.g. this turns [[17]] into 17).
    assert(cost.shape == ())

    return cost


## Backward propagation
# Build the linear part of backward propagation.
def linear_backward(dZ, cache):
    """
    Implement the linear portion of backward propagation for a single layer (l
ayer l)

    Arguments:
    dZ -- Gradient of the cost with respect to the linear output (of current l
ayer l)
    cache -- tuple of values (A_prev, W, b) coming from the forward propagatio
n in the current layer

    Returns:
    dA_prev -- Gradient of the cost with respect to the activation (of the pre
vious layer l-1), same shape as A_prev
    dW -- Gradient of the cost with respect to W (current layer l), same shape
as W
    db -- Gradient of the cost with respect to b (current layer l), same shape
as b
    """
    A_prev, W, b = cache
    m = A_prev.shape[1]

    dW = 1./m * np.dot(dZ,A_prev.T)
    db = 1./m * np.sum(dZ, axis = 1, keepdims = True)
    dA_prev = np.dot(W.T,dZ)

    assert (dA_prev.shape == A_prev.shape)
    assert (dW.shape == W.shape)
    assert (db.shape == b.shape)
```

```
    return dA_prev, dW, db


# Implement the backpropagation for the LINEAR->ACTIVATION layer.
def linear_activation_backward(dA, cache, activation):
    """
    Implement the backward propagation for the LINEAR->ACTIVATION layer.

    Arguments:
    dA -- post-activation gradient for current layer l
    cache -- tuple of values (linear_cache, activation_cache) we store for com
puting backward propagation efficiently
    activation -- the activation to be used in this layer, stored as a text st
ring: "sigmoid" or "relu"

    Returns:
    dA_prev -- Gradient of the cost with respect to the activation (of the pre
vious layer l-1), same shape as A_prev
    dW -- Gradient of the cost with respect to W (current layer l), same shape
as W
    db -- Gradient of the cost with respect to b (current layer l), same shape
as b
    """
    linear_cache, activation_cache = cache

    if activation == "relu":
        dZ = relu_backward(dA, activation_cache)
        dA_prev, dW, db = linear_backward(dZ, linear_cache)

    elif activation == "sigmoid":
        dZ = sigmoid_backward(dA, activation_cache)
        dA_prev, dW, db = linear_backward(dZ, linear_cache)

    return dA_prev, dW, db


# Implement backpropagation for the [LINEAR->RELU]  ××  (L-1) -> LINEAR -> SIG
MOID model.
def L_model_backward(AL, Y, caches):
    """
    Implement the backward propagation for the [LINEAR->RELU] * (L-1) -> LINEA
R -> SIGMOID group

    Arguments:
    AL -- probability vector, output of the forward propagation (L_model_forwa
rd())
    Y -- true "label" vector (containing 0 if non-cat, 1 if cat)
    caches -- list of caches containing:
                every cache of linear_activation_forward() with "relu" (there
 are (L-1) or them, indexes from 0 to L-2)
                the cache of linear_activation_forward() with "sigmoid" (there
is one, index L-1)

    Returns:
    grads -- A dictionary with the gradients
             grads["dA" + str(l)] = ...
             grads["dW" + str(l)] = ...
```

```
                grads["db" + str(l)] = ...
    """
    grads = {}
    L = len(caches) # the number of layers
    m = AL.shape[1]
    Y = Y.reshape(AL.shape) # after this line, Y is the same shape as AL

    # Initializing the backpropagation
    dAL = - (np.divide(Y, AL) - np.divide(1 - Y, 1 - AL))

    # Lth layer (SIGMOID -> LINEAR) gradients. Inputs: "AL, Y, caches". Output
s: "grads["dAL"], grads["dWL"], grads["dbL"]
    current_cache = caches[L-1]
    grads["dA" + str(L-1)], grads["dW" + str(L)], grads["db" + str(L)] = linea
r_activation_backward(dAL, current_cache, activation = "sigmoid")

    for l in reversed(range(L-1)):
        # lth layer: (RELU -> LINEAR) gradients.
        current_cache = caches[l]
        dA_prev_temp, dW_temp, db_temp = linear_activation_backward(grads["dA"
+ str(l + 1)], current_cache, activation = "relu")
        grads["dA" + str(l)] = dA_prev_temp
        grads["dW" + str(l + 1)] = dW_temp
        grads["db" + str(l + 1)] = db_temp

    return grads


#  Update parameters using gradient descent on every  W[l] and b[l] for l=1,
2,...,L.
def update_parameters(parameters, grads, learning_rate):
    """
    Update parameters using gradient descent

    Arguments:
    parameters -- python dictionary containing your parameters
    grads -- python dictionary containing your gradients, output of L_model_ba
ckward

    Returns:
    parameters -- python dictionary containing your updated parameters
                  parameters["W" + str(l)] = ...
                  parameters["b" + str(l)] = ...
    """

    L = len(parameters) // 2 # number of layers in the neural network

    # Update rule for each parameter. Use a for loop.
    for l in range(L):
        parameters["W" + str(l+1)] = parameters["W" + str(l+1)] - learning_rat
e * grads["dW" + str(l+1)]
        parameters["b" + str(l+1)] = parameters["b" + str(l+1)] - learning_rat
e * grads["db" + str(l+1)]

    return parameters
```

```
def predict(X, y, parameters):
    """
    This function is used to predict the results of a  L-layer neural network.

    Arguments:
    X -- data set of examples you would like to label
    parameters -- parameters of the trained model

    Returns:
    p -- predictions for the given dataset X
    """

    m = X.shape[1]
    n = len(parameters) // 2 # number of layers in the neural network
    p = np.zeros((1,m))

    # Forward propagation
    probas, caches = L_model_forward(X, parameters)


    # convert probas to 0/1 predictions
    for i in range(0, probas.shape[1]):
        if probas[0,i] > 0.5:
            p[0,i] = 1
        else:
            p[0,i] = 0

    #print results
    #print ("predictions: " + str(p))
    #print ("true labels: " + str(y))
    print("Accuracy: "  + str(np.sum((p == y)/m)))

    return p


def print_mislabeled_images(classes, X, y, p):
    """
    Plots images where predictions and truth were different.
    X -- dataset
    y -- true labels
    p -- predictions
    """
    a = p + y
    mislabeled_indices = np.asarray(np.where(a == 1))
    plt.rcParams['figure.figsize'] = (40.0, 40.0) # set default size of plots
    num_images = len(mislabeled_indices[0])
    for i in range(num_images):
        index = mislabeled_indices[1][i]

        plt.subplot(2, num_images, i + 1)
        plt.imshow(X[:,index].reshape(64,64,3), interpolation='nearest')
        plt.axis('off')
        plt.title("Prediction: " + classes[int(p[0,index])].decode("utf-8") +
" \n Class: " + classes[y[0,index]].decode("utf-8"))
```

4 - Two-layer neural network

Use the helper functions implemented before to build a 2-layer neural network with the following structure: *LINEAR -> RELU -> LINEAR -> SIGMOID*.

In [10]:
```
### CONSTANTS DEFINING THE MODEL ####
n_x = 12288     # num_px * num_px * 3
n_h = 7
n_y = 1
layers_dims = (n_x, n_h, n_y)
```

In [11]:

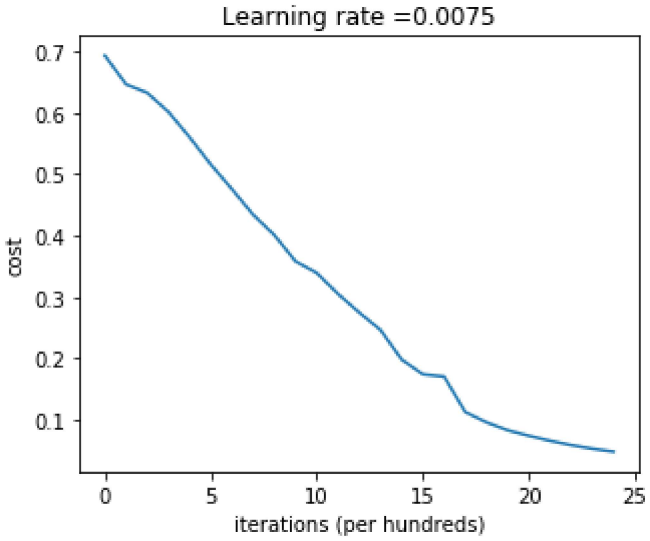
```
# GRADED FUNCTION: two_layer_model

def two_layer_model(X, Y, layers_dims, learning_rate = 0.0075, num_iterations
= 3000, print_cost=False):
    """
    Implements a two-layer neural network: LINEAR->RELU->LINEAR->SIGMOID.

    Arguments:
    X -- input data, of shape (n_x, number of examples)
    Y -- true "label" vector (containing 1 if cat, 0 if non-cat), of shape (1,
number of examples)
    layers_dims -- dimensions of the layers (n_x, n_h, n_y)
    num_iterations -- number of iterations of the optimization loop
    learning_rate -- learning rate of the gradient descent update rule
    print_cost -- If set to True, this will print the cost every 100 iteration
s

    Returns:
    parameters -- a dictionary containing W1, W2, b1, and b2
    """

    np.random.seed(1)
    grads = {}
    costs = []                                     # to keep track of the cost
    m = X.shape[1]                                  # number of examples
    (n_x, n_h, n_y) = layers_dims

    # Initialize parameters dictionary, by calling one of the functions you'd
 previously implemented
    ### START CODE HERE ### (≈ 1 line of code)
    parameters = initialize_parameters(n_x, n_h, n_y)
    ### END CODE HERE ###

    # Get W1, b1, W2 and b2 from the dictionary parameters.
    W1 = parameters["W1"]
    b1 = parameters["b1"]
    W2 = parameters["W2"]
    b2 = parameters["b2"]

    # Loop (gradient descent)

    for i in range(0, num_iterations):

        # Forward propagation: LINEAR -> RELU -> LINEAR -> SIGMOID. Inputs:
 "X, W1, b1, W2, b2". Output: "A1, cache1, A2, cache2".
        ### START CODE HERE ### (≈ 2 lines of code)
        A1, cache1 = linear_activation_forward(X, W1, b1, activation = "relu")
        A2, cache2 = linear_activation_forward(A1, W2, b2, activation = "sigmo
id")
        ### END CODE HERE ###

        # Compute cost
        ### START CODE HERE ### (≈ 1 line of code)
        cost = compute_cost(A2, Y)
        ### END CODE HERE ###
```

```
        # Initializing backward propagation
        dA2 = - (np.divide(Y, A2) - np.divide(1 - Y, 1 - A2))

        # Backward propagation. Inputs: "dA2, cache2, cache1". Outputs: "dA1,
 dW2, db2; also dA0 (not used), dW1, db1".
        ### START CODE HERE ### (≈ 2 lines of code)
        dA1, dW2, db2 = linear_activation_backward(dA2, cache2, activation =
"sigmoid")
        dA0, dW1, db1 = linear_activation_backward(dA1, cache1, activation =
"relu")
        ### END CODE HERE ###

        # Set grads['dWl'] to dW1, grads['db1'] to db1, grads['dW2'] to dW2, g
rads['db2'] to db2
        grads['dW1'] = dW1
        grads['db1'] = db1
        grads['dW2'] = dW2
        grads['db2'] = db2

        # Update parameters.
        ### START CODE HERE ### (approx. 1 line of code)
        parameters = update_parameters(parameters, grads, learning_rate)
        ### END CODE HERE ###

        # Retrieve W1, b1, W2, b2 from parameters
        W1 = parameters["W1"]
        b1 = parameters["b1"]
        W2 = parameters["W2"]
        b2 = parameters["b2"]

        # Print the cost every 100 training example
        if print_cost and i % 100 == 0:
            print("Cost after iteration {}: {}".format(i, np.squeeze(cost)))
        if print_cost and i % 100 == 0:
            costs.append(cost)

    # plot the cost

    plt.plot(np.squeeze(costs))
    plt.ylabel('cost')
    plt.xlabel('iterations (per hundreds)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    return parameters
```

The code below is to train parameters. See if the model runs. The cost should be decreasing. It may take up to 5 minutes to run 2500 iterations. If the "Cost after iteration 0" does NOT match the expected output below, click on the square (■) on the upper bar of the notebook to stop the cell and try to find the error.

In [12]:
```
parameters = two_layer_model(train_x, train_y, layers_dims = (n_x, n_h, n_y),
num_iterations = 2500, print_cost=True)
```

```
Cost after iteration 0: 0.6930497356599888
Cost after iteration 100: 0.6464320953428849
Cost after iteration 200: 0.6325140647912677
Cost after iteration 300: 0.6015024920354665
Cost after iteration 400: 0.5601966311605748
Cost after iteration 500: 0.5158304772764729
Cost after iteration 600: 0.47549013139433255
Cost after iteration 700: 0.4339163151225749
Cost after iteration 800: 0.400797753620389
Cost after iteration 900: 0.3580705011323798
Cost after iteration 1000: 0.3394281538366412
Cost after iteration 1100: 0.3052753636196263
Cost after iteration 1200: 0.27491377282130197
Cost after iteration 1300: 0.24681768210614846
Cost after iteration 1400: 0.19850735037466088
Cost after iteration 1500: 0.17448318112556663
Cost after iteration 1600: 0.17080762978096237
Cost after iteration 1700: 0.11306524562164721
Cost after iteration 1800: 0.09629426845937147
Cost after iteration 1900: 0.08342617959726861
Cost after iteration 2000: 0.07439078704319078
Cost after iteration 2100: 0.06630748132267926
Cost after iteration 2200: 0.059193295010381654
Cost after iteration 2300: 0.05336140348560552
Cost after iteration 2400: 0.04855478562877016
```



Now, use the trained parameters to classify images from the dataset. To see the predictions on the training and test sets, run the cell below.

In [13]:
```
predictions_train = predict(train_x, train_y, parameters)
```

```
Accuracy: 1.0
```

In [14]:
```
predictions_test = predict(test_x, test_y, parameters)
```

```
Accuracy: 0.72
```

5 - L-layer Neural Network

Use the helper functions that have been implemented previously to build an LL-layer neural network with the following structure: *[LINEAR -> RELU]*× ×*(L-1) -> LINEAR -> SIGMOID*.

In [15]:
```
### CONSTANTS ###
layers_dims = [12288, 20, 7, 5, 1] #  4-layer model
```

In [16]:

```
# GRADED FUNCTION: L_layer_model

def L_layer_model(X, Y, layers_dims, learning_rate = 0.0075, num_iterations =
3000, print_cost=False):#lr was 0.009
    """
    Implements a L-layer neural network: [LINEAR->RELU]*(L-1)->LINEAR->SIGMOI
D.

    Arguments:
    X -- data, numpy array of shape (number of examples, num_px * num_px * 3)
    Y -- true "label" vector (containing 0 if cat, 1 if non-cat), of shape (1,
number of examples)
    layers_dims -- list containing the input size and each layer size, of leng
th (number of layers + 1).
    learning_rate -- learning rate of the gradient descent update rule
    num_iterations -- number of iterations of the optimization loop
    print_cost -- if True, it prints the cost every 100 steps

    Returns:
    parameters -- parameters learnt by the model. They can then be used to pre
dict.
    """

    np.random.seed(1)
    costs = []                         # keep track of cost

    # Parameters initialization. (≈ 1 line of code)
    ### START CODE HERE ###
    parameters = initialize_parameters_deep(layers_dims)
    ### END CODE HERE ###

    # Loop (gradient descent)
    for i in range(0, num_iterations):

        # Forward propagation: [LINEAR -> RELU]*(L-1) -> LINEAR -> SIGMOID.
        ### START CODE HERE ### (≈ 1 line of code)
        AL, caches = L_model_forward(X, parameters)
        ### END CODE HERE ###

        # Compute cost.
        ### START CODE HERE ### (≈ 1 line of code)
        cost = compute_cost(AL, Y)
        ### END CODE HERE ###

        # Backward propagation.
        ### START CODE HERE ### (≈ 1 line of code)
        grads = L_model_backward(AL, Y, caches)
        ### END CODE HERE ###

        # Update parameters.
        ### START CODE HERE ### (≈ 1 line of code)
        parameters = update_parameters(parameters, grads, learning_rate)
        ### END CODE HERE ###

        # Print the cost every 100 training example
        if print_cost and i % 100 == 0:
```

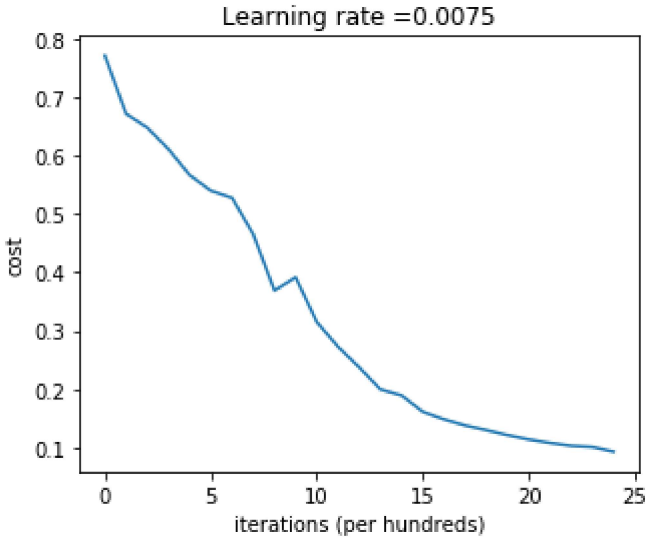
```
            print ("Cost after iteration %i: %f" %(i, cost))
        if print_cost and i % 100 == 0:
            costs.append(cost)

    # plot the cost
    plt.plot(np.squeeze(costs))
    plt.ylabel('cost')
    plt.xlabel('iterations (per hundreds)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    return parameters
```

Now train the model as a 4-layer neural network.

Run the cell below to train the model. The cost should decrease on every iteration. It may take up to 5 minutes to run 2500 iterations. Check if the "Cost after iteration 0" matches the expected output below, if not click on the square (■) on the upper bar of the notebook to stop the cell and try to find the error.

In [17]:
```
parameters = L_layer_model(train_x, train_y, layers_dims, num_iterations = 2500, print_cost = True)
```

```
Cost after iteration 0: 0.771749
Cost after iteration 100: 0.672053
Cost after iteration 200: 0.648263
Cost after iteration 300: 0.611507
Cost after iteration 400: 0.567047
Cost after iteration 500: 0.540138
Cost after iteration 600: 0.527930
Cost after iteration 700: 0.465477
Cost after iteration 800: 0.369126
Cost after iteration 900: 0.391747
Cost after iteration 1000: 0.315187
Cost after iteration 1100: 0.272700
Cost after iteration 1200: 0.237419
Cost after iteration 1300: 0.199601
Cost after iteration 1400: 0.189263
Cost after iteration 1500: 0.161189
Cost after iteration 1600: 0.148214
Cost after iteration 1700: 0.137775
Cost after iteration 1800: 0.129740
Cost after iteration 1900: 0.121225
Cost after iteration 2000: 0.113821
Cost after iteration 2100: 0.107839
Cost after iteration 2200: 0.102855
Cost after iteration 2300: 0.100897
Cost after iteration 2400: 0.092878
```



In [18]:
```
pred_train = predict(train_x, train_y, parameters)
```

```
Accuracy: 0.985645933014
```

In [19]:
```
pred_test = predict(test_x, test_y, parameters)
```

```
Accuracy: 0.8
```

It seems that the 4-layer neural network has better performance (80%) than the 2-layer neural network (72%) on the same test set.

6) Results Analysis

First, let's take a look at some images the L-layer model labeled incorrectly. This will show a few mislabeled images.

```
In [20]: print_mislabeled_images(classes, test_x, test_y, pred_test)
```

A few types of images the model tends to do poorly on include:

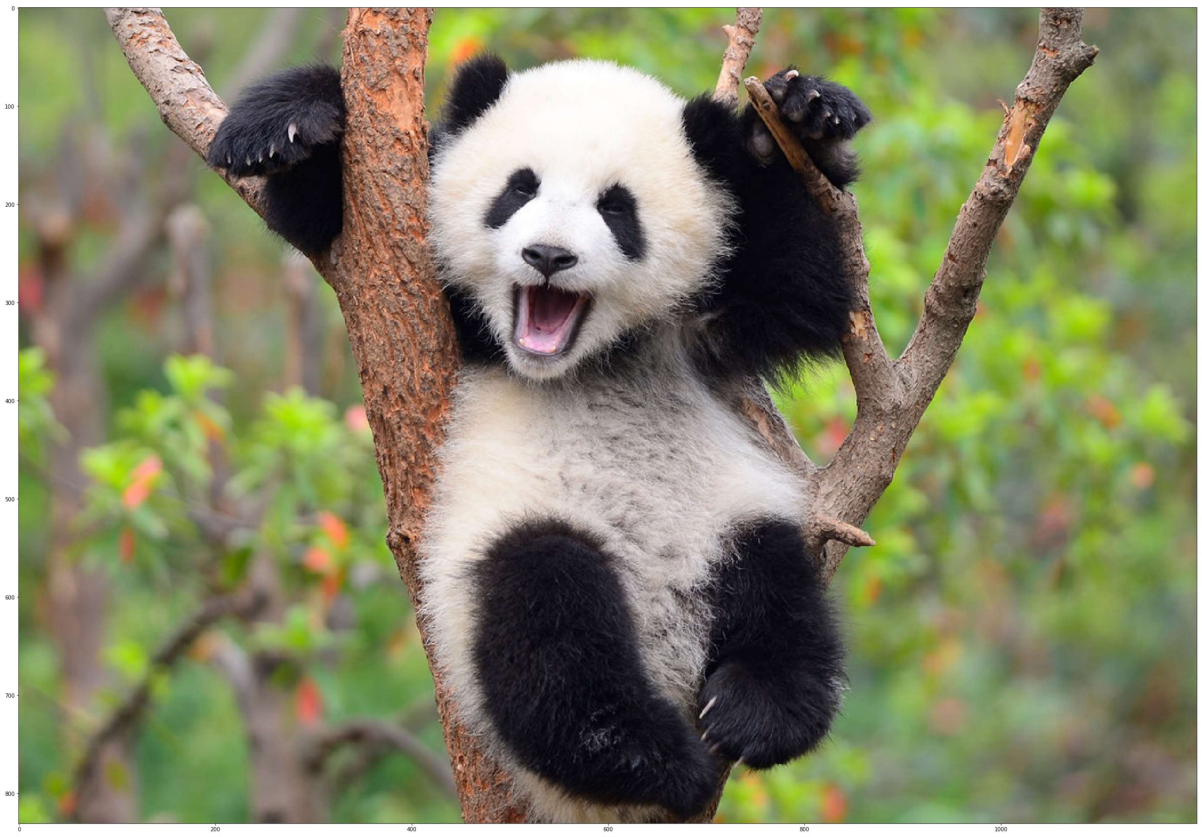
- Cat body in an unusual position
- Cat appears against a background of a similar color
- Unusual cat color and species
- Camera Angle
- Brightness of the picture
- Scale variation (cat is very large or small in image)

7) Test with other images

In [26]:

```
## START CODE HERE ##
my_image = "Panda.jpg" # change this to the name of your image file
my_label_y = [1] # the true class of your image (1 -> cat, 0 -> non-cat)
## END CODE HERE ##

fname = "images/" + my_image
image = np.array(ndimage.imread(fname, flatten=False))
my_image = scipy.misc.imresize(image, size=(num_px,num_px)).reshape((num_px*nu
m_px*3,1))
my_image = my_image/255.
my_predicted_image = predict(my_image, my_label_y, parameters)

plt.imshow(image)
print ("y = " + str(np.squeeze(my_predicted_image)) + ", your L-layer model pr
edicts a \"" + classes[int(np.squeeze(my_predicted_image)),].decode("utf-8") +
"\" picture.")
```

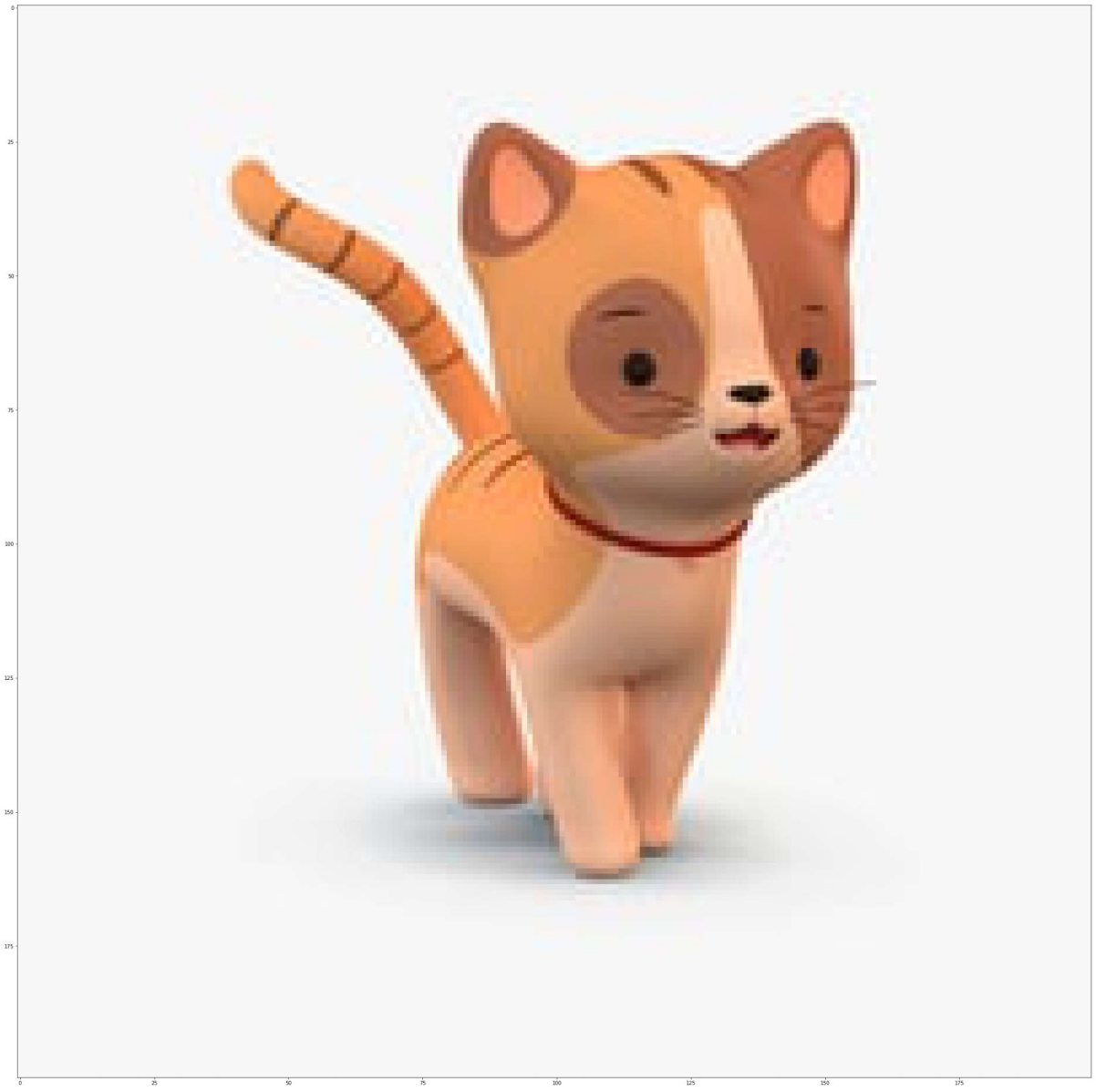
```
Accuracy: 0.0
y = 0.0, your L-layer model predicts a "non-cat" picture.
```



In [22]:

```
## START CODE HERE ##
my_image = "cat2.jpg" # change this to the name of your image file
my_label_y = [1] # the true class of your image (1 -> cat, 0 -> non-cat)
## END CODE HERE ##

fname = "images/" + my_image
image = np.array(ndimage.imread(fname, flatten=False))
my_image = scipy.misc.imresize(image, size=(num_px,num_px)).reshape((num_px*nu
m_px*3,1))
my_image = my_image/255.
my_predicted_image = predict(my_image, my_label_y, parameters)

plt.imshow(image)
print ("y = " + str(np.squeeze(my_predicted_image)) + ", your L-layer model pr
edicts a \"" + classes[int(np.squeeze(my_predicted_image)),].decode("utf-8") +
"\" picture.")
```

```
Accuracy: 1.0
y = 1.0, your L-layer model predicts a "cat" picture.
```



In [23]:

```
## START CODE HERE ##
my_image = "cat3.png" # change this to the name of your image file
my_label_y = [1] # the true class of your image (1 -> cat, 0 -> non-cat)
## END CODE HERE ##

fname = "images/" + my_image
image = np.array(ndimage.imread(fname, flatten=False))
my_image = scipy.misc.imresize(image, size=(num_px,num_px)).reshape((num_px*nu
m_px*3,1))
my_image = my_image/255.
my_predicted_image = predict(my_image, my_label_y, parameters)

plt.imshow(image)
print ("y = " + str(np.squeeze(my_predicted_image)) + ", your L-layer model pr
edicts a \"" + classes[int(np.squeeze(my_predicted_image)),].decode("utf-8") +
"\" picture.")
```

```
Accuracy: 1.0
y = 1.0, your L-layer model predicts a "cat" picture.
```

In [24]:
```
## START CODE HERE ##
my_image = "cat4.jpg" # change this to the name of your image file
my_label_y = [1] # the true class of your image (1 -> cat, 0 -> non-cat)
## END CODE HERE ##

fname = "images/" + my_image
image = np.array(ndimage.imread(fname, flatten=False))
my_image = scipy.misc.imresize(image, size=(num_px,num_px)).reshape((num_px*nu
m_px*3,1))
my_image = my_image/255.
my_predicted_image = predict(my_image, my_label_y, parameters)

plt.imshow(image)
print ("y = " + str(np.squeeze(my_predicted_image)) + ", your L-layer model pr
edicts a \"" + classes[int(np.squeeze(my_predicted_image)),].decode("utf-8") +
"\" picture.")
```

```
Accuracy: 1.0
y = 1.0, your L-layer model predicts a "cat" picture.
```

In [25]:

```
## START CODE HERE ##
my_image = "cl.jfif" # change this to the name of your image file
my_label_y = [1] # the true class of your image (1 -> cat, 0 -> non-cat)
## END CODE HERE ##

fname = "images/" + my_image
image = np.array(ndimage.imread(fname, flatten=False))
my_image = scipy.misc.imresize(image, size=(num_px,num_px)).reshape((num_px*nu
m_px*3,1))
my_image = my_image/255.
my_predicted_image = predict(my_image, my_label_y, parameters)

plt.imshow(image)
print ("y = " + str(np.squeeze(my_predicted_image)) + ", your L-layer model pr
edicts a \"" + classes[int(np.squeeze(my_predicted_image)),].decode("utf-8") +
"\" picture.")
```

```
Accuracy: 0.0
y = 0.0, your L-layer model predicts a "non-cat" picture.
```